The Poverty-GDP per capita-Health Triangle in Developing Countries Cyrine Hannafi^a and Christophe Muller^b

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Abstract

We estimate a dynamic system of simultaneous equations using country-level panel data from developing countries to identify the dynamic causal structural relationships between Poverty, GDP per capita and Health. For this, we develop innovative econometric methods for incomplete panel data to correct for endogeneity and the selectivity issues coming from missing data of poverty, and which have never been considered before. First, we find that the data generation of poverty indicators through household surveys depends positively on democracy and the level of wealth in the country. Furthermore, the probability to conduct a household survey in a given period is higher when a household survey has been conducted in the previous period. Moreover, we find that higher GDP per capita causes lower infant and child mortality rates but not necessarily poverty reduction. Our results highlight also the impact of health on GDP per capita and on the alleviation of poverty. Finally, we find no evidence about a significant influence of poverty on GDP per capita and health.

Keywords: Poverty, Economic growth, Health, Developing countries, Incomplete panel data, Simultaneous equations, Sample selection.

JEL Codes: C33, I19, I32, O11, O43.

1 Introduction

Eradicating poverty and improving health conditions are among the main Millennium Development Goals, and many efforts have been made by international organizations, governments and other development specialists to fight against poverty and health problems, in the developing world. Economic growth, as typically argued, is believed to play a major role in improving the living conditions of populations, in eradicating poverty and in promoting health. However, in many countries, economic growth is found to be accompanied with high levels of inequality and corruption, which may hamper its positive impact on human wellbeing.

Limiting the picture to the impact of economic growth on both poverty and health would miss the fact that health itself may contribute to growth through improvement of the labour force and productivity, which, in turn, should allow for the alleviation of poverty. Alternatively, better health may bust living standards if it contributes to lengthen life implying that some of the production output has to be shared with numerous unproductive elderlies.

At the same time, poverty may be a constraint to the proper functioning of the societies, decelerating economic growth and deteriorating health. In other words, both health and poverty may have strong impact on economic growth on the one hand, and on the other hand, they are themselves clearly connected, with poor people often having poor health and vice versa. That is why, we consider together the three factors poverty, economic growth and health, in a structural analysis of development.

The aim of the paper is, to provide answers to three questions. First, what is the impact of economic growth on human well-being, and specifically on poverty and health in the developing world? Second, is a country suffering from poverty and health problems able to achieve economic growth? Third, since poverty and health are themselves interconnected, is it rather the poverty that is harmful to health or health that has a strong impact on poverty or both?

There are only partial attempts in the literature to capture the structural linkages of these three dimensions, which were treated separately in the literature. The most common studies deal with the role of inequality in determining the impact of the economic growth on poverty. Moreover, the positive effect of economic growth on health has been more often investigated, especially for infant mortality. However, many researchers emphasise the role of health and human capital accumulation in the economic growth process. Others argue that health can increase fertility, which diminishes the share of the output allocated to each individual, hence the GDP per capita. Finally, there is less attention to the impact of poverty on economic growth and on the structural connections between poverty and health. Nevertheless, some findings in the literature emphasise the role of poverty in decelerating economic growth and health, which is shown itself to contribute to poverty reduction.

A major problem faced by the researchers investigating these questions, is missing data for poverty indicators in developing countries. The causes of this unavailability are likely to be related to diverse socio-economic characteristics of these countries, thereby generating selectivity biases. Furthermore, these missing data may constrain researchers to use incomplete panel data estimation methods. Our strategy is then to model the poverty data unavailability so as to correct for the selection biases. For this, we use recent advances in econometrics that allow us to account for unobserved dynamic dimensions on the selection process.

A second vital issue is the treatment of possible endogeneity problems. Introducing simultaneously poverty, health and GDP per capita implies to undertake a parallel search for appropriate instrumental variables that would be specific to each factor. If we take a look in the literature, this question is generally not well dealt with. At best, researchers merely resort to the use of the lagged endogenous variables as instruments.

We fill these gaps in the literature by constructing a model that simultaneously includes the three factors of interest (poverty, GDP per capita, health). We identify the two-way causalities between the factors, taking into account the selectivity problems of poverty indicators, panel incompleteness and endogeneity issues. First, we find that the data generation of poverty indicators through household surveys depends positively on democracy and the level of wealth in the country. Furthermore, the probability to conduct a household survey in a given period is higher when a household survey has been conducted in the previous period. Moreover, we find that higher levels of GDP per capita cause lower infant and child mortality rates but does not reduce poverty significantly. Moreover, health indicators massively improve GDP per capita and alleviate poverty. However, a new finding is the absence of clear evidence about the effect of poverty on economic growth, and that of poverty on health.

The rest of this paper proceeds as follows. Section 2 discusses the framework and the literature. Section 3 describes our empirical framework and the econometric methodology. Section 4 presents our empirical results. Section 5 reports robustness checks. Finally, we discuss the main findings in Section 6 and we conclude in Section 7.

2 The Framework and the Literature

Diagram 1 provides a synthetic description of the main plausible interactions between the three factors. We summarize the empirical results found in the literature in Table 1, for the relationships studied between each pair of two factors of the triangle.

In every country, economic growth allows the government to spend more on health services, education, infrastructure and social programs, thereby improving the country's standards of living and reducing unemployment and poverty. Moreover, the Trickle Down Theory (Aghion and Bolton (1997)) states that the poor may also gain when the rich get richer. This may occur through capital accumulation, higher economic activity and more jobs, and also through new opportunities for poor people to borrow and to invest.

The arguments given before concur with the ones given by some economists studying the impact of economic growth on poverty, while they also emphasise the role played by inequality. A first trend of the literature claims that "growth is good for the poor". According to Bhalla (2002) and Sala-i-Martin (2002), economic growth is sufficient to reduce poverty. Furthermore, Dollar and Kraay (2002, 2013) showed that the incomes of the poor, in the lowest quintile, rise on average equiproportionately with average incomes.

A second approach insists on inequality as a constraint to poverty reduction through growth. Ravallion (2005) claims that "Inequality is bad for the poor". Precisely, using country level data, his estimated rate of poverty reduction through growth depends greatly and negatively on the inequality level. Ravallion and Datt (1991), Ravallion (2001) and Bourguignon (2004) all emphasize that both economic growth and inequality reduction can generate substantial poverty reduction.

On the other hand, poverty can hamper savings, which makes it harder to finance productive investment and may lead to slow economic growth. Moreover, poverty can lead to less education, making poor countries lie behind in terms of human capital accumulation. Few studies deal with the impact of poverty on economic growth. Ravallion (2012) showed that, in developing countries, the initial poverty rate has a sizeable negative impact on the growth rate at any initial mean consumption level. Lopez and Serven (2009) argue that poverty can diminish investment, especially in contexts of low-level financial development, which can be harmful for economic growth.

Health may also benefit from economic growth, for example through higher financial resources to improve sanitation and nutrition conditions, and higher investment in the health sector. An extensive literature addresses this relationship using a variety of health indicators. For instance, Younger (2001), using infant mortality as a measure of aggregate health level for an unbalanced panel of 82 Demographic and Health Surveys, does not find any evidence of an impact of economic growth on health, when including country fixed effects. He argues that economic growth does not vary enough in the set of countries included, which makes it behave like a fixed effect and the impact of economic growth on health disappears. Moreover, he concludes that income is not a strong determinant of children's health status. However, Pritchett and Summers (1993) show that income is a determinant factor in reducing infant mortality in the developing world, but find that its impact on life expectancy at birth is smaller. The same result is also found by Hanmer, Lensink and White (2003) who insist on health conditions and educational variables as explanatory factors of infant mortality in the developing countries.

Conversely, better health of the population may help to generate growth and prosperity. Good children health impacts positively their learning abilities and leads to better educational outcomes. It may raise the incentives for greater investment in education and may lower fertility according to Becker's trade-off between quality and quantity of children. Furthermore, good health of workers facilitates higher productivity, more creativity and better adaptation to technologies (Bloom, Canning and Sevilla (2004), Aghion, Howitt and Murtin (2010)). However, Acemoglu and Johnson (2006, 2013) find no evidence about the impact of health on economic growth. They argue that a rise in life expectancy at birth leads to an increase in population, not enough compensated by the decline in birth rate, which depletes economic growth because of higher levels of unemployment and a decrease in the share of consumption resources. These findings are criticized by other researchers, as by Bloom and Canning (2014), who argued that Acemoglu and Johnson's model does not control for institutional variables and initial population, life expectancy and income. They also showed that improvements in the health status leads to an increase in income levels when controlling for conditional convergence. In a precedent work published in 2004, Bloom and Canning used a production function approach and showed that a one-year improvement in life expectancy leads to an increase of 4 per cent in the output. Again, Howitt and Murtin (2011) show that the impact of health on economic growth is larger when introducing both the initial level of life expectancy at birth and its changes. However, they find no impact when eliminating the initial level of life expectancy from the regression of health on economic growth, which shows that both initial level of health and its accumulation are determinant for economic growth. Lorentzen, McMillan and Wacziarg (2008), using adult and infant mortality rates as measures of aggregate ill-health, argue that physical investment and fertility are major channels through which health can impact economic growth. In other words, high adult mortality rates may lead to less investment by decreasing the incentives to invest in human and physical capital. High infant mortality can stimulate fertility, which leads to less investment in education and human capital since high levels of infant mortality rates make people care rather for having more children rather having well-educated children, consistently with the quantity-quality trade-off of Becker (1974). Furthermore, Cervellati and Sunde (2011) use a panel database of 47 countries over the period 1940-1980 and find, based on a theoretical model that links life expectancy at birth and income, that, for countries, that had not started the demographic transition, an increase in life expectancy at birth spans population growth, reducing economic growth because of fewer opportunities to work and a lower share of available resources. However, this effect is reversed for the countries, having completed the transition. This is because the increase in life expectancy at birth is rather accompanied with higher investment in human capital accumulation and lower fertility, stimulating economic growth. Such mixed effects of life expectancy at birth on economic growth are also found by Bhargava, Jamison, Lau and Murray (2001), using adult survival rates as proxies for health status in 92 countries over the period 1965-1990.

People suffering from poor health may receive lower earnings also because they can work fewer hours. Moreover, they may have higher health expenses, for example to buy medicines or pay for doctor visits. As a consequence, their savings will be lower and they are more likely to fall into poverty. Poverty can be harmful to health, especially to child health, by causing malnutrition and diseases because of the lack of satisfaction of basic needs in food, sanitation and healthy environment. Furthermore, some poor people cannot afford good education, which prevents them to reach a good understanding of diseases and other health problems (Xavier Sala-i-Martin (2002)). These bidirectional relationship between health and poverty are studied in the literature considering the possibilities of a two-way causality. These studies generally deal with South Asia or Sub-Saharan Africa, which suffer particularly from poor health and poverty. For instance, using the 1999 South African integrated family survey, Godlonton and Keswell (2005) consider the body mass index as the health indicator and use Probit models to explain poverty and health status. They found a positive association between health and poverty status of the surveyed households. Households who include more unhealthy individuals are sixty per cent more likely to be income poor than those who include fewer unhealthy individuals. They argue that that health affects poverty by improving productivity and the educational outcomes.

For the reverse effect of poverty on health, Rajan, Kennedy and King (2013) show, for 17 states of India, that low poverty and high literacy rates strongly and positively impact

health, when regressing the number of deaths and the under-five mortality rate on the poverty gap indicator and the literacy rate, with a greater effect of literacy. Klasen (2007) claims that there is no econometric evidence about the effect of poverty on health when introducing economic growth as an additional determinant of health using undernourishment rates, childhood underweight indicators and under-five mortality rates for a panel of developing countries over the period 1990-2000. He explains this result by the multi-colinearity existing between poverty and economic growth indicators, that may hide the effect of poverty on health. Furthermore, Pe, Wall and Perrson (2000), examine in Nicaragua from 1988 to 1993 the association between poverty, social inequity and maternal education with infant mortality and show that higher absolute level of poverty increases the risk of infant mortality. We now turn to the empirical strategy.

As we mentioned before, the relationships between Poverty, GDP per capita and Health were treated separately in the literature and almost no studies considered them simultaneously. An exception is Gupta and Mitra (2004), who, for fifteen Indian states, used structural equations to show that economic growth and health are positively linked in the two-way directions. Precisely, they found that economic growth is a strong determinant of life expectancy, enhancing health, which in turn promotes economic growth by increasing productivity and capability to work. Moreover, they showed that that poverty reduction in India is more due to the improvement in the health status rather than to economic growth. They argue that unless economic growth is accompanied with better opportunities for poor people to work, we cannot expect a reduction of poverty through economic growth.

3 Empirical Strategy

3.1 Database construction

Poverty statistics are generally based on income and expenditure household surveys conducted by government statistical agencies. As mentioned before, in developing countries, these surveys are typically implemented every five or ten years at best. Moreover, there is no correspondence of the years with available poverty statistics across countries. For our analysis, we consider the poverty headcount index with 1.25 \$ a day as poverty line, which is the most popular poverty indicator. We use GDP per capita as an indicator of the country's general living standard and a proxy for economic development. For health, we consider the infant and child mortality rates since these indicators are available for almost all developing countries. Furthermore, major causes of infant and child mortalities may be predominantly and directly related to living conditions and health infrastructure. For instance, almost 70 per cent of infant and child deaths cases would have been avoided if good health infrastructure and adequate living conditions had been available $(WHO)^1$. We also use life expectancy at birth as a health indicator as it is commonly used by researchers. However, this indicator is based on the mortality rates for the whole population, for which the causes of death are not only related to living conditions, but also substantially to other factors such as unpredictable diseases and accidents. Furthermore, its construction involves information on death events before the considered year. Therefore, life expectancy at birth is just included to assess

¹http://www.who.int/en/.

whether the results change or not with changing the health indicator.

We gather annual (incomplete) panel data from World Development Indicators of the World Bank² for the period 1980-2013 and 137 developing countries (Sample 1). The choice of the period of study is constrained by the data availability of poverty indicators for which the first observations only occur in 1980.

Second, taking into account that household surveys are not run each year, we divide the data of the study into longer time intervals, as many researchers did (Dollar and Kraay (2013), Lopez and Serven (2009)). The division is based on the average gap existing between poverty observations for each country. As a result, we divide the data, into 8 periods of 4 years. We obtain a number of poverty observations that ranges from 0 to 8, for any given country. After some data cleaning, our final sample includes 113 countries and 8 periods of 4 years from 1980 to 2013 (Sample 2). This sample is used in the first step of the estimation, in which we model the survey incidence (Section 3.2.1).

Third, in order to estimate the simultaneous system for the three factors, we keep only the observations for which the poverty estimate is available from Sample 2. Moreover, we keep only countries with at least 3 available observations, as some of our estimators require at least two lags of the poverty indicator (detailed in section 3.2.2). Finally, we obtain an incomplete panel database of 75 countries and 231 observations (Sample 3).

Table 2 reports descriptive statistics for the variables used in our estimation. Starting with the poverty headcount index, there are, on average, almost 20 per cent of people living under 1,25 \$ a day, in developing countries over the studied period, using Sample 1. However, some countries have in some years zero per cent as the estimated poverty headcount index value with this poverty line. This is the case mainly in some countries in Europe and Central Asia, such as Montenegro and Turkey, in 2008 and 2009. In contrast, the highest values of the poverty headcount index corresponds to countries in Sub Saharan Africa, such as Guinea with almost 92 per cent in 1991 and Madagascar with 81 per cent in 2010.

If we take a look at GDP per capita, we have a mean of 2054 \$ with a large dispersion in the between dimension. This is because many countries have a very low level of GDP per capita such as Burundi with just 155 \$ in 2013, and they are regrouped with countries with an upper-middle income, such as Turkey with 8716 \$ in the same year. Note that the countries with low poverty levels are not necessarily the richest ones. For instance, Jordan has an estimated poverty headcount index of 0,07 per cent in 2008, with a GDP per capita a little more than the mean, at 2727 \$ in the same year.

For the health indicators, the infant mortality rate is on average 55 infants per 1000 for infant mortality rate, 82 per 1000 for mortality under five years rate, and about 62 years life expectancy at birth. We find high levels of infant mortality in many countries of Sub-Saharan Africa, such as Sierra Leone with 107 per 1000 as infant mortality rate in 2013 and 45 years as life expectancy at birth in 2012. However, other countries, such as Belarus and Montenegro have less than 5 per 1000 for the infant mortality rate and about 70 years for the life expectancy at birth in 2013. Most of variation in the indicators lies in the between dimension, which suggests a strong need for fixed effects in the model specification. However,

 $^{^{2}} https://data.worldbank.org/data-catalog/world-development-indicators.$

there is still within variation to allow for dynamic modelling and estimation.

When comparing sample 1 to sample 2, we obtain almost the same standard deviations. That is that the variability across years is small and little information is lost by using fouryears periods. However, when we go from Sample 2 to Sample 3, the mean levels of GDP per capita or the infant mortality rate substantially change. In sample 3, we have higher means of GDP per capita (2513 \$) and the life expectancy at birth (67 years) and a lower level of infant mortality (47.98 per 1000) and mortality under 5 (69.50 per 1000). The selection leaves only 75 countries in sample 3, which represents about 66 per cent of the total number of countries (113 countries in sample 2). Clearly, these figures should point to the possibility of selectivity biais in studies restricting their sample to the availability of poverty indicators as is usual.

Table 3 shows the distribution of the two samples across regions. In sample 1, Sub-Saharan Africa represents 37 per cent of the developing countries with only 19 per cent of the available observations for poverty. In sample 2, after dividing the period of study into 8 periods of 4 years, Sub-Saharan Africa has 27 per cent of the available observations for poverty. Furthermore, we obtain a higher weight of the other regions after the division into 8 periods of 4 years. For instance, Latin America and Carribean represents almost 19 per cent of the developing world. Finally, the percentage of the available observations of poverty statistics goes from 35 per cent to 24 per cent when moving from Sample 1 to Sample 2. Since sample 3 includes only the available observations of poverty statistics, the weight of each region is the percentage of the available observations of poverty statistics reported for Sample 2.

3.2 Econometric strategy

We now discuss our econometric strategy. For this, we specify a system of simultaneous dynamic equations for incomplete panel data. Each factor is determined by its lagged value and the two other lagged factors of the triangle as follows :

 $\begin{aligned} Poverty &= \beta_{01} + \beta_{11}LagPoverty + \beta_{21}LagGDP/capita + \beta_{31}LagHealth + \epsilon_1, \\ GDP/capita &= \beta_{02} + \beta_{12}LagPoverty + \beta_{22}LagGDP/capita + \beta_{32}LagHealth + \epsilon_2, \\ Health &= \beta_{03} + \beta_{13}LagPoverty + \beta_{23}LagGDP/capita + \beta_{33}LagHealth + \epsilon_3, \end{aligned}$

where *Poverty* is the poverty headcount index with 1,25 \$ a day as poverty line. *GDP/capita* is the GDP per capita and *Health* is the health indicator, which is either the infant mortality rate per 1000 infants or the mortality rate under 5 years old per 1000 or the life expectancy at birth. β_{ij} , i = 0, 1, 2, 3, j = 1, 2, 3, are parameters to estimate and ϵ_1 , ϵ_2 , ϵ_3 are centred error terms, which are assumed to satisfy semi-parametric restrictions appropriate for the used estimation methods. For example, strict exogeneity is assumed when applying within-group estimators.

However, as we mentioned before, selecting only the available observations for poverty indicators may generate a form of a selection bias that needs to be corrected. This unavailability led us to search for the social and economic factors behind it, which had never been done before in the literature. To do so, we specify in a first step a model that explains this selectivity. In a second step, we shall correct for this selection bias in the estimation of the dynamic system.

3.2.1 First step : Model of Survey Incidence

In this part, we consider Sample 2 that contains the complete panel data of 113 countries and 8 periods of four years each, in order to explain the data unavailability of the poverty headcount index with 1.25 \$ a day as the poverty line. Let y_{it} be the dummy variable that takes the value 1 or 0 if there is an available observation for country i and period t, or not, respectively.

• A dynamic econometric model:

We introduce some dynamics in the model when explaining y_{it} by considering two opposite hypotheses. The first one assumes that conducting a household survey in a given period should facilitate the process of conducting another one in the next period since many steps have been already done in the previous survey such as the analysis of the population's structure by administrative divisions in a given country that would allow for sampling. However, a second hypothesis supposes that the occurrence of a survey should make more likely the postponement of the next household survey as they are costly to run and the collected information loses its interest over time.

We use the quadratic exponential model developed recently by Bartolucci and Nigro (2010). who propose a quadratic exponential approximation in order to capture the unobserved heterogeneity between the countries in a dynamic framework for a discrete choice model. This approach is easy to apply and imposes few restrictions as compared to the other estimators of the dynamic logit model proposed in the literature (Chamberlain, 1985, Honoré and Kyriazidou, 2000, Carro, 2007). In particular, Chamberlain (1985) does not allow for covariates in the model estimation. Moreover, Honoré and Kyriazidou (2000) includes exogenous covariates but is applied with at least three periods and does not consider time-dummy variables. In contrast, Bartolucci and Nigro model allows for time-dummy variables and does not require any assumption on the distribution of the heterogeneous individual intercepts, nor on their correlations with the covariates introduced. It also performs better in terms of efficiency than the alternative approaches. Hence, it allows for further economic interpretations and more efficient estimators, in comparison with the other models in the literature. The quadratic exponential model has a similar form to that of the dynamic fixed-effects logit model, while it is instead based on an additional term measuring the effect of the present choice on the expected utility of the next occasion. In other words, if this correction term is positive, the choice of today has a positive impact on the expected utility of tomorrow.

Let x_{it} be a vector of strictly exogenous covariates, the model assumes that $y_{it} = \mathbf{1} \{y_{it}^* \ge 0\}$, with a linear equation for the latent variable :

$$y_{it}^* = \alpha_i + x_{it}^{'}\beta_1 + y_{i,t-1}\gamma + e_t^*(\alpha_i, X_i) + \epsilon_{it}$$
, for i=1,..., n and t=1,...T,

where the error terms ϵ_{it} have standard logistic distribution and are independent, and the α_i are individual-specific intercepts. The additional term $e_t^*(\alpha_i, X_i)$ measures the effect of the present choice on the expected utility of the next occasion t+1. X_i is the vector of exogenous covariates, with the lead form in the additional term.

$$\begin{array}{l} \text{For } \mathrm{t} < \mathrm{T}, \ \mathrm{let} \ e_t^*(\alpha_i, X_i) = log \frac{1 + exp \left[\alpha_i + x_{i,t+1}' \beta_1 + e_{t+1}^*(\alpha_i, X_i) + \gamma \right]}{1 + exp \left[\alpha_i + x_{i,t+1}' \beta_1 + e_{t+1}^*(\alpha_i, X_i) \right]}, \ \mathrm{and} \\ e_T^*(\alpha_i, x_i) = \phi + x_{iT}' \beta_2. \end{array}$$

The conditional maximum likelihood estimator of $\theta = (\beta'_1, \beta'_2, \phi, \gamma)'$ is obtained by maximizing the conditional log-likelihood $l(\theta)$ using a simple iterative algorithm of Newton Raphson where :

$$l(\theta) = \sum_{i} 1 \{ 0 < y_{i\downarrow} < T \} \log [p_{\theta}(y_i | X_i, y_{i0}, y_{i\downarrow})], \ y_{i\downarrow} = \sum_{t} y_{it}$$

The calculation of the term p_{θ} is described in the Appendix.

• Controls and Endogeneity :

Returning to the empirical model, we suspect that the richer developing countries may have more resources that may allow them to conduct surveys more easily. Hence, GDP per capita is included as an independent variable in the latent equation for survey incidence, as an indicator of a country's economic capacity to run surveys. Moreover, the presence of democracy can influence these data availability through a higher governmental motivation to run household surveys. Indeed, poverty alleviation policies is a core topic of political debates, except perhaps in dictatorial regimes and these surveys are necessary for monitoring these policies. Furthermore, we include variables describing country-level shocks that may hamper the data collection process, such as natural disasters or social and political shocks like violent conflicts. However, the variable GDP per capita may be endogenous when explaining survey incidence because of the multiplicity of interconnected variables and possible omitted confounding factors. Precisely, GDP per capita may be strongly affected by natural disasters and social and political shocks. As a response to this issue, we use the control function approach proposed in Papke and Wooldridge (2008), which is based on two steps. In the first step, we estimate the reduced form of the suspected endogenous variable using the appropriate instrument, and adding the other exogenous variables of the model. The second step consists in computing the residual errors from this first step and introducing them in the latent equation in order to test and correct for the endogeneity. Hence, the latent equation takes the following form:

$$y_{it}^* = \alpha_i + x_{itExog}^{'}\beta_1 + x_{itEndog}^{'}\beta_2 + y_{i,t-1}\gamma + e_t^*(\alpha_i, X_i) + Residendog_{it}\delta + \epsilon_{it},$$

where the α_i are the individual specific intercepts, and x_{itExog} and $x_{itEndog}$ are respectively the exogenous and endogenous covariates. Residendog_{it} are the residuals computed from the following first-stage equation estimated using a fixed effects estimator :

$$x_{itEndog} = \eta_i + x_{itExog}' \lambda + z_{it}' \phi + \xi_{it},$$

where the η_i are the individual specific intercepts and z_{it} is a vector of exogenous instrument for the endogenous variables $x_{itEndog}$, ϵ_{it} and ξ_{it} are error terms, and β_1 , β_2 , γ , δ , λ and ϕ are parameters to estimate.

The choice of the instruments is a crucial step. In this first-step model, exogenous instruments must be found that impact GDP per capita, but does not affect significantly the probability of conducting a household survey in a given country. After several attempts, we retain as an instrument the price of oil multiplied by a positive or negative sign, depending on whether the country is an exporter or an importer of oil. The intuition behind this is that a higher price of oil causes a higher national income for oil exporter countries. However, the same higher price of oil is negative for oil-importer countries, not only because of additional costs, but also because it stimulates inflation, thereby leading to a decrease in consumers' expenditures and then a deceleration in economic growth (Hamilton (1983), Rotemberg and Woodford (1996)).

• Selectivity correction term

Finally, we compute the inverse Mills' ratio λ_{it} from the above first-step estimation in order to correct the selectivity bias in the main simultaneous system that is expanded in a second step below. The seminal method of selectivity correction, based on the two-step estimation of Heckman (1979), was later developed by Lee (1983) who generalised the correction procedure for non-normal distribution. Among diverse other attempts of correcting selectivity in linear systems, Dubin and McFadden (1984) used the multinomial logit model to model selection and explain residential demand for appliance and electricity. In the US, Bourguignon, Fournier and Gurgand (2007) studied this approach based on a multinomial logit in the first stage with Monte Carlo comparisons.

However, selectivity correction may be more complex when considering dynamic panel data models because it may involve some dynamics from observed or unobserved variables. Wooldridge and Semykina (2013) explained how to handle selectivity issues for dynamic panel data by using first-stage estimation of probit models, but the approach is too simple, based first on computing the inverse Mills ratio from a first step probit estimation for each cross section. Second, it consists of including it in the basic equation with the first difference to estimate the dynamic panel, using GMM. In contrast, our model allows first for the dynamic estimation in the first step. Moreover, we correct for selectivity in a simultaneous system of dynamic equations taking into account endogeneity problems. We should mention that no study tried to handle the same selection issue in the framework of a system of panel data simultaneous equations. We fill this gap and now discuss this.

3.2.2 Second step (Simultaneous system):

In this part, we use Sample 3, that contains the incomplete panel database of 75 countries and 231 observations, after selecting from Sample 2 only the observations for which we have poverty data.

For the selection bias correction, we introduce the previously estimated inverse Mills ratio λ_{it} in the poverty equation directly, and its lagged value in the two other equations in which

poverty is included as an explicative variable with its lagged value. Indeed, the selectivity due to missing poverty data is contemporary to the poverty regressor in the GDP per capita and health equations. Therefore, the system to estimate is, for each country i and period t :

$$ln(Poverty_{it}) = \beta_{0i1} + \beta_{11}ln(Poverty_{i(t-1)}) + \beta_{21}ln(GDP/cap_{i(t-1)}) + \beta_{31}ln(Health_{i(t-1)}) + \gamma_1\lambda_{it} + \epsilon_{it1} (1)$$

 $ln(GDP/cap_{it}) = \beta_{0i2} + \beta_{12}ln(Poverty_{i(t-1)}) + \beta_{22}ln(GDP/cap_{i(t-1)}) + \beta_{32}ln(Health_{i(t-1)}) + \gamma_2\lambda_{i(t-1)} + \epsilon_{it2}$ (2)

 $ln(Health_{it}) = \beta_{0i3} + \beta_{13}ln(Poverty_{i(t-1)}) + \beta_{23}ln(GDP/cap_{i(t-1)}) + \beta_{33}ln(Health_{i(t-1)}) + \gamma_{3}\lambda_{i(t-1)} + \epsilon_{it3} (3)$

where β_{0i1} , β_{0i2} , β_{0i3} are the fixed effects, β_{11} , β_{21} , β_{31} , β_{12} , β_{22} , β_{32} , β_{13} , β_{23} , β_{33} , γ_1 , γ_2 , γ_3 are coefficients to estimate and ϵ_{it1} , ϵ_{it2} , ϵ_{it3} are centred error terms for each equation. Note that the introduction of exogenous factors, such as geographical shocks, demographic factors, conflict variables, etc, does not yield significant results. For this reason, the model is limited to the variables of interest. However, exogenous control variables will be introduced in the robustness subsection 5.3 later on.

• Econometric model :

As we mentioned before, almost no studies considered simultaneously the three dimensions of interest. Gupta and Mitra (2004), for fifteen Indian states, used three stage least squares for estimating structural equations of GDP per capita, infant mortality and poverty. They used expenditure on poverty as instrument to poverty, urbanisation, infrastructure and industrialisation as instruments to economic growth and finally per capita health expenditure is used as instrument to health. Most econometricians used similar estimation approaches : GMM (Dollar and Kraay (2002, 2013), Lopez and Serven (2009), Acemoglu and Johnson (2006, 2013)), Fixed and random effects estimators for panel data (Aghion, Howitt and Murtin (2011), Rajan, Kennedy and King (2013)).

We endeavour to take further this line of research by specifying a three dimensional structural system and estimating it with state-of-the-art econometric methods, using Sample 3, with only the observations for which poverty data are available. Precisely, we generalise the fixed effects three-stage-least squares (FE3SLS) for dynamic panel data with endogenous regressors (Baltagi and Deng (2012)) by dealing with the endogenous incompleteness of the dynamic panel data, and with a specific instrumentation strategy. This is supported by the results of adjusted Hausman tests of fixed effects versus random effects, which lead us to adopt in each case the fixed effects model.

Let $\tilde{Y} = \begin{pmatrix} \tilde{Y}_1 \\ \tilde{Y}_2 \\ \tilde{Y}_3 \end{pmatrix}$ be the matrix of the dependent variables for each equation after apply-

ing the within-group transformation. That is: \tilde{Y}_1 , \tilde{Y}_2 , and \tilde{Y}_3 are respectively $ln(Poverty_{it})$, $ln(GDP/cap_{it})$, $ln(Health_{it})$, each transformed with the within-group transformation based

on the unbalanced data.

Let
$$\tilde{Z} = \begin{pmatrix} Z_1 & 0 & 0 \\ 0 & \tilde{Z}_2 & 0 \\ 0 & 0 & \tilde{Z}_3 \end{pmatrix}$$
 be the matrix of explanatory variables and selectivity correction

terms for each equation, from respectively equations (1), (2) and (3), after applying the within-group transformation. That is: \tilde{Z}_1, \tilde{Z}_2 and \tilde{Z}_1 includes the within-group transformation lagged dependent variable for the considered equation, the two other variables of the triangle and the inverse Mills' ratio in each equation. Note that because of missing poverty data at same periods, matrix \tilde{Z} corresponds to unbalanced panel data in general. In particular, the number of periods involved in the within-group transformation may vary across countries and factors.

Let $\hat{\sum}_{v} = \begin{pmatrix} \hat{\sigma}_{v11}^{2} & \hat{\sigma}_{v12}^{2} & \hat{\sigma}_{v13}^{2} \\ \hat{\sigma}_{v21}^{2} & \hat{\sigma}_{v22}^{2} & \hat{\sigma}_{v23}^{2} \\ \hat{\sigma}_{v31}^{2} & \hat{\sigma}_{v32}^{2} & \hat{\sigma}_{v33}^{3} \end{pmatrix}$ be the estimator of the covariance matrix of the errors of

the simultaneous system, for each country.

The $\hat{\sigma}_{vij}^2$ are computed from the respective residuals of preliminary FE2SLS (Fixed effects two-stage least-squares) estimations of equation i (e_i) and that of equation j (e_j) , (i, j = 1, 2, 3) from equations (1), (2) and (3), as follows:

$$\hat{\sigma}_{vij}^2 = \frac{e_i^{'}e_j}{\sqrt{(N-n-k_i)(N-n-k_j)}}$$

where N is the total number of observations, n is the number of countries, k_i and k_j are the number of parameters in equation i and equation j, respectively.

Let $\tilde{H} = \begin{pmatrix} \tilde{H}_1 & 0 & 0\\ 0 & \tilde{H}_2 & 0\\ 0 & 0 & \tilde{H}_3 \end{pmatrix}$ be the matrix of the instruments for each equation, after applying

the within-group transformation, where H_i is the list of instruments for each equation i, (i = 1, 2, 3), with the within-group transformation. It includes a matrix of internal instruments for the lagged dependent variable for the considered equation and two other external instruments for each of the two other factors of the triangle poverty, GDP per capita and health, considered as endogenous. Further details of the instrumental strategy are reported in the next part of this sub subsection.

Accordingly to Baltagi and Chang (2000), we use the following operators for the calculation of the final estimator:

Q is the matrix of the within-group transformation, that is : $Q = I_N - P$, $N = \sum_{i=1}^n T_i$, n is the number of countries (47 in our case), I_N is the identity matrix of dimension N. $P = diag(\bar{J}_{T_i})$, $\bar{J}_{T_i} = \frac{1}{T_i}(J_{T_i})$, J_{T_i} is a matrix of ones of dimension $T_i \times T_i$. T_i is the number of periods for country *i*. 'diag' means a diagonal matrix.

The selectivity correction fixed effects three-stage least-squares' estimator with incomplete panel and endogeneity problems is computed as follows :

$$\hat{\beta}_{FE3SLS} = \left[\tilde{Z}'\tilde{H}\left(\tilde{H}'\left(\hat{\Sigma}_{v}\otimes Q\right)\tilde{H}\right)^{-1}\tilde{H}'\tilde{Z}\right]^{-1}\left[\tilde{Z}'\tilde{H}\left(\tilde{H}'\left(\hat{\Sigma}_{v}\otimes Q\right)\tilde{H}\right)^{-1}\tilde{H}'\tilde{Y}\right].$$

• Choice of instruments

An important ingredient of our econometric approach is the choice of the instrumental variables. First, we follow Arellano and Bond (1991) and Blundell and Bond (1998) in order to instrument the lagged dependent variable $(y_{i(t-1)k})$ in each equation k, (k = 1, 2, 3), (i = 1, ..n) and $(t = 1, ..T_i)$ by using interval instruments. This part of the instrumentation is based on a matrix with a specific form that includes past observations of the dependent variable for the considered equation k, ranging from the lag of order 2 to the earliest available lag in the data. Namely, the matrix of the interval instruments for the lagged dependent variable in each structural equation k is constructed from the following matrix M_{ik} for each country i and equation k:

$$M_{ik} = \begin{pmatrix} y_{i1k} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1k} & y_{i2k} & \dots & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & y_{i1k} & \dots & y_{i(T_i-2)k} \end{pmatrix}.$$

Since we have incomplete panel data, each M_{ik} is adjusted to the size of the longest matrix containing the dependent variable ranging from the lag of order 2 to the earliest available lag in the data for a country j. Precisely, we retain the size, $T_j - 2$ of the country j, containing the highest number of available time observations for the poverty indicator and we add zeros for the missing values, for the other countries that have a lower number of available time observations. The final matrix of instruments is :

M_{l}	$_{k} = \left(M_{1}^{\prime}\right)$	$_k, \dots N$	I_{jk}^{\prime},N	$M_{nk}^{'}$										
	$\int y_{11k}$		0		0	 y_{i1k}		0	 0	 y_{n1k}		0		0
	0		0		0	 0		0	 0	 0		0		0
	0		y_{11k}		$y_{1(T_1-2)k}$	 			 	 				
	0	0	0	0	0	 			 	 				
_	0	0	0	0	0	 			 	 0		y_{n1k}		$y_{n(T_n-2)k}$
_	0	0	0	0	0	 			 	 0	0	0	0	0
	0	0	0	0	0	 			 	 0	0	0	0	0
	0	0	0	0	0	 			 	 0	0	0	0	0
	0	0	0	0	0	 			 	 0	0	0	0	0
	0	0	0	0	0	 			 	 0	0	0	0	0
	0	0	0	0	0	 0	0	y_{j1k}	 $y_{j(T_j-2)k}$	 0	0	0	0	0

The moment conditions for each country i, in equation k are written as follows : $E(M'_{ik} * \epsilon_{ik}) = 0$, where $\epsilon_{ik} = (\epsilon_{i3k}, ..., \epsilon_{iT_ik})'$ is the vector of the error terms, for the country i, in equation k, from the third period of observation to the last available one (We have T_i observations for each country i).

Second, beyond the use of the lags for internal instruments for the lagged dependent variable, we also use some information as external instrumental variables for each of the two other factors of the triangle poverty, GDP per capita and health, considered as endogenous in each equation. This fills a gap in the literature since most studies resort simply to instrumentation based on the lags of the endogenous variables (Dollar and Kraay (2002, 2013), Lopez and Serven (2009), Bloom and Canning (2004). Doing so is not necessarily easy because there may be interactions with more than one lag. This means that the lagged endogenous variable, used as instrument in equation k, can be correlated with the dependent variable y_{itk} , when the interaction between the endogenous variable and y_{itk} is not simultaneous and is persistent over time, which violates the instrument's specification, which is the absence of a causality from the instrument to the dependent variable. For instance, if the initial level of GDP per capita has a long term impact on the level of poverty that takes place even after three or four periods, the lagged GDP per capita at order 2, used as instrument, would impact the level of poverty in the poverty equation. Thus, it cannot be considered as a valid instrument for the lagged GDP per capita, considered as endogenous in the poverty equation.

Few studies use external instruments in order to handle endogeneity issues in the kind of equations we are interested in. For instance, Younger (2001) uses the terms of trade as an instrument for the usual GDP per capita in order to study the impact of economic growth on health. Pritchett and Summers (1993) use the same instrument with adding investment. However, these instruments may be endogenous because of potential two-causality existing with GDP per capita. Furthermore, Acemoglu and Johnson (2006, 2013) construct a predicted mortality rate variable based on interventions for diseases since 1940 in 75 countries from all regions of the world, and use it as an instrument for changes in life expectancy at birth when studying the impact of health on economic growth. They claim to find no evidence of a significant impact of health on economic growth. These results are criticized by Bloom and Canning (2014) who show the weakness of the instrument used by Acemoglu and Johnson with introducing the initial level of life expectancy in the equation, which made the impact become significantly positive. Furthermore, Lorentzen, McMillan and Wacziarg (2008) use adult and infant mortality instrumented with the malaria ecology index in order to identify the channels through which health can impact growth. Godlonton and Keswell (2005) identify the relationship between health and poor status by using a depression index (which describes the mental health of the members of the same household) and access to sanitation as instruments for health.

Returning to our approach, we keep the same instrument constructed in the first step for GDP per capita. Precisely, it is based on the hypothesis that the price of oil affects economic growth according to whether the country is oil-importer or oil-exporter, but does not have a direct link with poverty or health processes.

For health, the main instrument retained is the amount of foreign aid devoted directly to health, which is obtained from the AIDDATA database.³ This database gathers diverse sources of foreign aid information notably describing the country receiving the aid, the donors and many details of aid programs. Precisely, we select the aid programs that are targeted to the health sector (interventions against epidemics, health care, medicines) and that should not have or have little direct connections with poverty or economic growth. However, this instrument may be invalid if aid is allocated according to the level of health problems in the recipient country. Hence, we adjust this instrument by using instead exogenous shocks on

 $^{^{3}}$ http://aiddata.org/.

these targeted foreign aid programs based on the financial crises that the donor countries faced, which impacted their aid flows. Precisely, for the countries that have received foreign aid, we gather the list of the donor countries for each country. Hence, if at least one of the donor countries have faced a financial crisis in one of the period considered in our study and available for this country, the instrument takes the value 1, 0 otherwise. The same work is done for each country in order to construct the instrumental variable. However, we are aware that these financial crises that the donor countries have experienced may potentially also impact indirectly the level of economic growth for the countries receiving the aid if aid is given under some commitment conditions and conventions, such as trade exchanges, or is given in the form of loans. Nevertheless, we consider that the latter issues may be neglected in our application.

Finally, our harder task is to find instruments for poverty that are not directly correlated with economic growth or health. For this, we exploit again the AIDDATA database and consider rather foreign aid flows directed to low-cost housing. This kind of aid is targeted mainly to people suffering from bad housing conditions, to disaster victims, and homeless people. Again, we deal with the same problem of potential endogeneity of this instrument by using instead exogenous shocks based on financial crises in the donor countries, following the same methodology as for the health instrument.

• Comparison with panel Var model

The simultaneous structural system of the three variables poverty, GDP per capita and health is similar to a panel VAR model. However, the structural model differs from a simple VAR estimation. First, VAR estimation is typically used to deal with stationarity problems in panel data and to distinguish between short and long run. In this paper, we do not consider these questions. Moreover, in a VAR model, all the variables are endogenous while there is no case of instrumentation since each endogenous variable is explained by the other ones and its dynamics from a long term cointegration prospective. For panel VAR models, there are some attempts to take into account heterogeneity and fixed effects while most studies focus instead on error variance decomposition and impulse response functions' estimation. For instance, Pedroni (2013) estimates, through a panel VAR system, shocks and impulse response functions with distinguishing between individual structural shocks and common shocks with allowing for heterogeneity of the dynamics in response to the shocks. Moreover, Abrigo and Love (2016) takes into account fixed effects and resort simply to equation-byequation GMM estimation with instrumenting the dynamics in each equation by past levels. We apply this second VAR approach to our model but almost we do not find any significant coefficient. This is may be due to the fact that this estimation lacks of precision, especially with neglecting the simultaneity between the three equations and the endogeneity problems in our data. In contrast, our model encounters these issues and allows for better efficiency.

• Impulse response functions

We report as a last step from the estimated system, impulse response functions for the estimated structural model in order to simulate the response functions of each variable to a positive shock on the other. Graph 1 reports the figures of the IRFs functions, for 4 successive periods.

We now turn to the estimation results.

4 The Results

4.1 Selectivity equation

This step is crucial for obtaining satisfactory estimations because without selectivity correction, the results are non sensical. Therefore, the first motivation fact is bias correction. However, we also want to investigate the factors behind the availability of poverty indicators, using state-of-the-art techniques for binary variable panel data.

The estimates of the survey incidence model are reported in Table 4. Column (1) reports the equation for the GDP per capita with the exogenous regressors and its instrument (the price of oil multiplied by a positive or negative sign depending on whether the country is exporter or importer of oil). The exogenous regressors are democracy, disasters and conflicts that may have an effect on GDP per capita, as natural and political shocks. This estimation is performed using the fixed effects estimator. The coefficient of the instrument is significant and negative at the 1 per cent level. Hence, an increase in the price of oil reduces the level of the GDP per capita for importers of oil.

The residuals of this first estimation, are computed and introduced in the base model presented in Column (2), in which the binary indicator of poverty data availability is explained by using the quadratic exponential logit estimator proposed by Bartolucci and Nigro (2010). It turns out that there is no significance of the coefficient associated with the computed residuals, which suggests the exogeneity of the GDP per capita variable in the survey incidence model. Furthermore, the lagged dependent binary variable appears with a positive coefficient that is significant at the 5 per cent level. This implies that the probability to conduct a household survey in a given period is increased when a household survey is conducted in the previous period. That may be due to knowledge accumulation in the process of surveys. The positive coefficient for the lagged GDP per capita, which is significant at the 10 per cent level, confirms the hypothesis that the richest developing countries benefit from their larger economic resources to conduct surveys. Moreover, the coefficient associated to democracy is positive and significant at the 5 per cent level. The more extensive freedoms of opinion and of investigation in democracies, allied to governments being held responsible before parliaments in this context, may explain the better reliability of their public statistics.

Finally, the variable conflicts appears with a non significant coefficient in our model. However, there is a positive coefficient for natural disasters, which is significant at the 1 per cent level. It may be that countries suffering from natural disasters arise more interest from donors, of which aid programs are often monitored using household surveys. The last column of the table reports the results for a fixed effects logit model without correction of endogeneity. We obtain reverse results than before: the coefficient of the lagged

GDP per capita which becomes no significant and the coefficient of the lagged dependent variable now appears with a negative sign. This shows how much the results are sensitive to controling for the dynamics and the endogeneity in the econometric method.

4.2 Simultaneous system

Tables 5, 7 and 9 report the estimates of the three-dimensional system, respectively for the Poverty, GDP per capita and Health equations, using our selectivity correction fixed effects three stage least squares with incomplete panel and endogeneity and varying the health indicator (We use infant mortality rate, mortality under five and life expectancy ate birth). For comparison, the first column of each table reports the same results but with only the two-dimensional system including poverty and GDP per capita (The same formula is used for the estimator but with only two equations). This is because we want to assess what the differences are made by introducing health in the system. Moreover, Tables 6, 8 and 10 report the estimates of the same equations using the fixed effects estimator in the first three columns of each table (without simultaneity, selectivity correction and endogeneity). Columns 4, 5 and 6 report the results with taking into account only simultaneity and not endogeneity. Moreover, columns 7, 8 and 9 report the two-stage-least-squares estimates that do not take into account simultaneity (only endogeneity). Finally, columns 10, 11 and 12 report that of the fixed effects three-stage least-squares without taking into account selectivity.

Beginning with the results reported in Table 5, we clearly can see the high significance of the inverse Mills' ratio's coefficient, which is robust to changes in the health indicator. This confirms the importance of correcting selectivity, while this has been neglected so far in the current literature. However, the introduction of the health factor in the system weakens the estimated coefficient of the lagged dependent variable for poverty, although this varies with the chosen health indicator. Precisely, the coefficient of the lagged dependent poverty variable is negative and significant at the 1 per cent level only when using life expectancy at birth. So, we cannot make unambiguous conclusions about the direction of the impact of the lagged dependent variable for poverty. This is in adequacy of the main findings of Ravallion (2012) about the poverty convergence. Precisely, he argues that both high initial poverty rate and high incidence of poverty to achieve higher level of poverty reduction than the other countries, starting with lower levels of poverty incidence. In other words, there is no poverty convergence, which explains the non-significance of the lagged dependent variable on poverty.

Considering the impact of GDP per capita on poverty, the introduction of the health factor makes the coefficient of the lagged GDP per capita become no significant when using infant mortality under either one or five years as the health indicator. However, it is negative and significant at the 1 per cent level with life expectancy at birth. As we mentioned before, we prefer the results with the infant mortality rates, which reflect better the health status of the country, and which are based on actual indicators rather than estimations. Moreover, the results show that only the introduction of infant and child mortality rates, as pure indicators of health status has a strong impact on the whole system estimation. However, life expectancy at birth remains problematic because it is not just an indicator of good-health status, but recovers other phenomena such as the global size of labour force and also return on investment in children.

These results found are in adequacy with the approach that insists on the role of income inequality in decelerating poverty reduction through growth. That is to say that there is a great impact of GDP per capita on poverty when it is based on equity and improvement of the living conditions. Otherwise, if the income distribution is unequal, the share of the income going to the poor would be lower than that expected, with less opportunities for poor people to work and to improve their living conditions. Moreover, it may be also due to high levels of corruption that do not allow for a better profitability from economic growth in order to alleviate poverty in the country. Therefore, we can say that, in the context of developing countries, economic growth is not pro-poor, perhaps because there is much corruption and income inequality working against eradicating poverty.

Coming to the impact of health on poverty, it is strongly negative and robust in all specifications. We have positive and significant coefficients at the level of 1 per cent for the two infant mortality rates, under one and five years, with almost the same value. For instance, an increase in the infant mortality rate by 1 per cent leads to an increase in the level of poverty by almost 2,3 per cent. Consistently, we also obtain negative coefficients of the effect of the life expectancy at birth. The high level of significance of the coefficients of the health indicators is consistent with poor health being associated with a worse access to jobs, lower earnings and less health care, increasing the probability of falling into poverty.

When we compare these results with those reported in Table 6, we can clearly see the dramatic changes when substituting the econometric approach. Accounting for simultaneity clears almost all the effects of all variables in the poverty equation, with greater coefficient values. Furthermore, it yields significant coefficients for the lagged dependent variable of poverty. Moreover, the correction of endogeneity brings the same changes in terms of significance, but with eliminating the significance of the coefficient of the effect of GDP per capita on poverty when using life expectancy at birth, as the health indicator.

Taking into account both endogeneity and simultaneity reverses the sign of the coefficient of the lagged dependent variable for poverty and the impact of GDP per capita on poverty becomes significant and negative with life expectancy at birth. However, when we correct for selectivity, we see that this correction helps us to elicit the effect of health on poverty by increasing the values of coefficients of the health factor estimated in the poverty equation. Moreover, the coefficient of the lagged dependent variable for poverty, becomes non significant when using any of the two child mortality indicators.

Table 7 reports the estimation results for the equation of GDP per capita, which are almost the same for the diverse specifications obtained by changing the health indicator. We obtain significant results for the coefficients of the inverse Mills' ratio and the coefficients of the lagged dependent variable. Some economic growth convergence is found, as typical in the empirical studies based on GDP per capita and its lag.

However, the results show no impact of poverty on GDP per capita. This relationship was little investigated in the literature. The channel through which we expected to obtain significant and negative impact is savings that decrease with poverty, which can hamper investment and thereby economic growth. The absence of evidence about this effect may be due to the weakness of the financial sector in developing countries and the absence of a culture of savings.

Moreover, the impact of health on GDP per capita is positive, significant and robust to all specifications. For instance, an increase by 1 per cent of the level of infant mortality under one, or five years, leads to a decrease in the GDP per capita by almost 0,52 per cent. Furthermore, the impact is stronger with life expectancy at birth. An increase in the level of life

expectancy at birth by 1 per cent can increase GDP per capita by 3 per cent on average. Comparing with Table 8, we can see that the results are almost the same in terms of significance and signs. Both the correction of endogeneity and the introduction of simultaneity allow us to exhibit a positive impact of poverty on GDP per capita, which is however, repealed by the correction of selectivity. Furthermore, we obtain higher coefficients' values for the impact of the lagged dependent variable and the impact of health on GDP per capita with the selectivity correction.

Table 9 displays the results for the health equation. Beginning with the inverse Mills' ratio, the associated coefficient is significant only when using life expectancy at birth as health indicator. Nevertheless, since the Inverse Mills' ratio has significant coefficients in the two first equations, the selectivity correction remains interesting and more than fundamental. Moreover, We have positive coefficients significant at the 1 per cent level for the lagged dependent variable for all the chosen health indicators.

For the impact of poverty on health, we have significant and negative coefficients only when using life expectancy at birth but only with small effects. Perhaps, in the context of developing countries, one should rather consider other health indicators that reflect better the health status as malnutrition indicators, infectious diseases incidence, children weight, etc, because maybe, poverty may cause directly malnutrition and limited access to basic needs and suitable living conditions, hence health problems, rather than leading directly to the death of infants and children.

Moreover, the impact of GDP per capita on health is negative and significant at the 10 per cent level when using the infant mortality rates. For instance, an increase by 1 per cent of the GDP per capita leads to a decrease of infant mortality rates by approximately 0,17 per cent. We conclude that the level of development in the country strongly determines health statuses especially for children. Higher levels of economic growth help governments to generate higher investment in health services and infrastructure, thereby improving living conditions and providing better health care for infants and children.

When comparing with Table 10, we find almost the same results in terms of significance and signs. However, the most relevant difference that we observe is the impact of poverty on health when using life expectancy at birth and which becomes significant only when the selectivity correction is performed.

Finally, Graph 1 reports the impulse response functions (IRFs) of each factor to a positive shock on a given factor. The shocks are calibrated to be equal to one empirical standard deviation for the shocked variable. We interpret only the IRFs for the significant effects, obtained from our basic estimation. First, the IRF corresponding to the lagged dependent variable for GDP per capita (IRF from GDP per capita to GDP per capita), shows that the IRF is positive at the first period, than decreases slightly and increases since the second period with an acceleration in the third period. The impact of a shock on GDP per capita is persistent over time and still increases even after four periods, which corresponds to sixteen years. Second, the IRF from GDP per capita to infant mortality is negative and decreases persistently with a slight attenuation in the second period to attain less than -0,12 point in the fourth period.

For the IRFs that correspond to a shock on infant mortality rate, the Graph shows first that, the positive impact on poverty is low in the first period (with only 0,01 point) but increases considerably with a slight attenuation since the second period. Moreover, the same shock on

infant mortality affects strongly GDP per capita with a decreasing negative impulse response function to attain less than -0,1 in the fourth period. Finally, the impact of a shock on infant mortality is persistent over time with a positive increasing IRF, accelerated since the second period to attain almost 0,12 points after four periods.

5 Robustness Checks

5.1 Sargan test

First, we check for the system identification of the three equations of poverty, GDP per capita and health. The order condition that should be verified is that we have a number of endogenous variables, that is inferior to that of exogenous variables in the system. Since we include 23 instruments for each variable (21 for the dynamics and 2 for the other two endogenous variable), this condition is verified. However, the system is over- identified. Hence, we test the validity of the instruments in each equation by using Sargan test (Sargan 1958) that we adjust to our estimation system. The test statistic is : $\frac{\hat{\varepsilon}' P_H \hat{\varepsilon}}{\hat{\sigma}^2}$ where $\hat{\varepsilon}$ is the estimated residual vector from each equation of the system (The Poverty, GDP per capita and Health equations), $P_H = H(H'H)^{-1}H'$ where, H is the matrix of instruments and $\hat{\sigma}^2$ is the estimated variance of the residuals. This computed statistic follows, under the Null Hypothesis, a $\chi^2(r)$ distribution with r equal to the number of extra instruments. The instruments are valid under the Null Hypothesis. In our case, the number of extra instruments is 20. The test statistics and the p-values are shown in the last lines of Tables 5, 7 and 9, allowing us not to reject the null hypothesis of the instruments validity in most of the cases, mainly in the health and the GDP per capita equations.

5.2 Further Instruments

In this part, we report additional results obtained when using other instruments for our endogenous variables, notably for health and poverty (Tables 11, 12, 13). In particular, we introduce interactions of the foreign aid variables for health and low cost housing with the variable describing the financial crises in the donor countries ('Instrumentation 2' in the tables). Moreover, we also consider as an instrument for poverty, the percentage of households led by a female head. The intuition behind this is that households whose head is female face higher risk of falling into poverty, because women have fewer opportunities to work, especially in developing countries, which are suffering from women discrimination. However, this instrument may be invalid if the female headed household pay less attention to their children health when the head is working.

Nevertheless, we estimate our model considering this variable as instrument for poverty. We estimate also the same model with the amount of aid for health as an instrument for poverty ('Instrumentation 3' in the tables).

When comparing these results with the previously reported baseline results, we find qualitatively almost the same directions of results, when we use the interactions of the amounts of aid with financial crises as instruments. However, with female headed household and the amount of aid for health as instruments, we find a new significant and negative impact of GDP per capita on poverty with all the health indicators. In particular, we obtain negative and significant coefficients at the levels of 5 and 1 per cent with a greater effect when using life expectancy at birth. In this last case, an increase in the level of GDP per capita by 1 per cent diminishes poverty by 2,29 per cent. Considering the impact of poverty on economic growth, with this same instrumentation, we obtain significant but positive coefficients. Moreover, we obtain a positive and significant coefficient at the 10 per cent level with mortality under five years for the impact of poverty on health, and no impact of GDP on health with any of the three health indicators.

We conclude that the results are sensitive to the instruments introduced. In particular, the introduction of female headed household, as instrument for poverty, gives different results but remains suspect because of its potential effect on infant and child health statuses. That's why, we are so careful in choosing appropriate instruments. Precisely, we tried to exogenise as possible, the instruments for both health and poverty indicators with using the crises suffered by the donor countries, for both the health and housing aids. Meanwhile, the female headed household instrumental variable remains problematic, impacting potentially children health.

5.3 Control variables

In this subsection, we discuss some results achieved when adding control variables to our simultaneous system estimation (Last three columns of Tables 11, 12, 13). First of all, we include the adolescent fertility rate, extracted from the World Bank database.⁴ The intuition behind this is that young parents are more likely to fall into poverty especially in the context of developing countries. Precisely, these parents had sexual relationships before marriage so they are often rejected by their families and then unable to take responsibilities at an early age. Moreover, adolescent fertility can lead to premature birth, which may augment infant mortality. This variable can also affect educational attainment because young mothers leave school in the most cases. Even though this indicator may be endogenous in the sense that adolescent fertility may be related to the level of education, it is interesting to assess if its inclusion changes the results.

Furthermore, we include in the three equations a few institutional variables from the Worldwide Governance Indicators 2013 (Kraay and Mastruzzi 2010). On the one hand, we select two indicators from this database in both poverty and health equations. First, we introduce the 'voice and accountability' indicator, which reflects the degree of freedom (freedom of association, expression, media, participating in selecting government). Moreover, we consider the degree of corruption from the same database. On the other hand, in the GDP per capita equation, we include an indicator of political stability, denoted 'Political stability' which proxies the degree to which the government can be sensitive to violent actions and terrorism. We also include an indicator of the private sector development, denoted 'Private Sector Development', which measures the performance and the competitiveness of the private sector that promotes economic growth and investment. All the variables mentioned range from -2.5 (weak) to 2.5 (strong) for government performance regarding each criteria. However, the endogeneity of these indicators may be more severe in the GDP per capita equation, if richer countries have more resources to fight terrorism, but also to promote the private sector. Though, as above, it seems still interesting to check if their inclusion affects the results. Finally, we add rural population as a regressor in order to check

⁴https://data.worldbank.org/.

whether a higher number of people living in rural areas is associated or not with higher levels of poverty, worse health status and lower GDP per capita.

The findings are qualitatively identical to those obtained from the estimation without control variables, in terms of both significance and signs in the three equations. The only cases in which the results dramatically change are those of the effect of health on poverty when using life expectancy at birth, and that of poverty on health when using the same indicator. Precisely, the associated coefficients become non significant. This may be due to possible endogeneity problems for adolescent fertility, which may be the consequence of low education levels, and may affect poverty and health. Indeed, the coefficients remain significant when we remove this variable from the estimation.

The results show strong impacts of the adolescent fertility rate in the three equations with the expected signs (positive for poverty and child mortalities, negative for GDP per capita). However, we find no effect when using life expectancy at birth in the health equation. It means that young parents are more likely to fall into poverty, being unable to take responsibilities at an early age. Moreover, adolescent fertility can lead to premature birth, which may augment infant and child mortality rates, rather than life expectancy at birth. This variable can also affect educational attainment, hence impacts the level of GDP per capita. Concerning the institutional variables, we find only a significant and positive coefficient for the corruption indicator in the poverty equation when using life expectancy at birth. We obtain the same result in the health equation when using infant mortality. This result indicates that a higher level of corruption in a given country may increase inequality and reduce social programs and spending on infrastructure and health, which leads to poverty increase and deterioration of health statuses, especially for children. Finally, we find a significant negative coefficient for the share of rural population in the poverty equation, which indicates that people living in rural areas are less vulnerable to poverty, maybe because these people can afford their basic needs in terms of food from agriculture.

On the whole, it seems fair to say that most results from the dynamic system estimation are robust to the introduction of the control variables.

6 Discussion

The paper attempts to provide a global picture on the development process by adressing three questions. First, the role of economic growth on fighting poverty and promoting health in the developing world. Second, we ask whether a country suffering from poverty and health problems is able to achieve economic growth or not. Third, since poverty and health are themselves interconnected, we investigate whether it is poverty that is harmful for health, or health that has a strong impact on poverty or both. In other words, the paper aims at estimating the multiple causalities among Poverty, Economic Growth proxied by GDP per capita and Health in a dynamic simultaneous system.

To do so, we argue first that the unavailability of poverty indicators, in the developing world is not random and that there exist socio-economic factors behind the incidence of poverty data, which can lead to selectivity biases that we correct in this paper for the first time in the literature. We use the quadratic exponential model developed recently by Bartolucci and Nigro (2010) and the control function approach of Papke and Wooldridge (2008) to explain poverty data incidence in the developing countries, accounting for dynamics and potential endogeneity problems. First, our results show the relevance of our selectivity correction strategy and its high level of significance in studying the simultaneous system. Not only the selectivity correction increases the magnitude of some major coefficients but it also changes the significance of other coefficients like that of the lagged dependent variable in the poverty equation. Neglecting this correction would have led to biased and misleading estimates of the factors of the triangle.

We find that the probability to conduct a household survey in a given period is increased when a household survey has been conducted in the period before. Second, we find that the countries that are economically more developed with more resources conduct more surveys. This may reflect the investment in buildings, capital, labour force and know-how that is involved in the surveys conducted by statistical offices. Third, we find that democratic countries allow for more freedom in collecting data and have greater needs of statistics, in part because government policies are controlled by the parliament based on statistical information. Finally, the results show that the countries suffering from natural disasters have a higher probability of conducting these surveys, perhaps because statistical surveys are often counterparts required by aid donors.

In order to analyze the Poverty-GDP per capita-Health triangle, we correct first for selectivity bias from the first step estimation and use state-of-the-art econometric methods to estimate a simultaneous system of three equations.

The first result highlighted by the correction of selectivity bias is that there is no clear effect of the lagged dependent variable for poverty, which rejoins the findings by Ravallion (2012) who claims that there is no poverty convergence.

For the other two factors, GDP per capita and health indicators, our results confirm those found in the literature about the impact of the lagged dependent variable. In other words, the initial levels of GDP per Capita, infant mortality rates and life expectancy at birth matter for economic growth and health improvement.

We find that the introduction of the health factor in the triangle squarely changes the picture. The impact of economic growth on poverty is hindered by including health indicators in the system estimation, with using infant and child mortality rates for the health indicator. This result indicates that economic growth is generally not pro-poor which is consistent with the high degrees of corruption and income inequality in the developing countries, which are obstacles to poverty alleviation. The same result was also found by Gupta and Mitra (2004) using the same indicators for economic growth and poverty. Moreover, it is in adequacy with the literature that insists on the role of income inequality in decelerating poverty reduction through growth, for example by Ravallion (2005) who claims that "Inequality is bad for the poor". Moreover, Ravallion and Datt (1991), Ravallion (2001) and Bourguignon (2004) emphasize that both economic growth and inequality changes can generate substantial poverty reduction. On the contrary, economic growth is found in our estimations, to have a massive positive effect on health statuses, when using infant mortality rates. The same results were found by Pritchett and Summers (1993), Hanmer, Lensink and White (2003), and Gupta and Mitra (2004). Higher levels of economic growth may make governments invest more in health services and medical infrastructure, thereby improving living conditions and providing better health care for infants and children, rather than directly reducing the poverty rate. The second question of the paper was about the impact of health and poverty on economic growth. The paper shows no impact of poverty on GDP per capita. This may be due to the weakness of the financial sector in developing countries and the culture of savings. However, these findings are in contradiction with the results found in Ravallion (2012) who shows that the initial poverty rate has a sizeable negative impact on the economic growth rate. This same result was also found by Lopez and Serven (2009). Our progress is again through the introduction of the health factor that changes the picture of the development process. The positive impact of health on GDP per capita is strong and robust to the choice of the health indicator. These results are at odds with those found by Acemoglu and Johnson (2007) who claim that there is no evidence about this impact, but it rejoins those found in other studies about the role of human capital accumulation, notably those of Bloom and Canning (2004, 2014), Lorentzen, McMillan and Wacziarg (2008), and Gupta and Mitra (2004).

The third question is about the interactions between poverty and health statuses. Our results show first the negative impact of health on poverty that is obvious for both the infant mortality rates and the life expectancy at birth. It may be that poor health is associated with a lower access to jobs, lower earnings and health care, increasing the probability to fall in poverty. The same results were also found by Gupta and Mitra (2004) when using infant mortality rate, and by Goldton and Keswell (2005) when using rather the body-mass index as the health indicator. However, we find no evidence of the effect of poverty on infant mortality. These results rejoin that found by Klasen (2007) when controlling for the level of GDP per capita in the same equation and using infant mortality rates. We argue that, maybe, poverty can affect directly health status through malnutrition, diseases, low children weights, etc, but does not necessarily lead to the infant mortality.

Let us now emphasize a few salient findings from all the estimation results. First, poverty appears mostly as an outcome of the development process instead of a full-fledged factor. It is determined by the living standard levels and the health levels, but do not cause them. It is even doubtful that there is some substantial inertia of poverty along time, at least that is not obvious from the estimated system. The fact that the initial poverty does not much affect the growth processes, poverty processes or health processes, contradicts some trends in the literature that views poverty situations as a direct obstacle to development, as in Ravallion (2012).

The fact that we cannot see poverty convergence, while there is probably growth or living standards convergence across countries, may be partly due to the fact that economic growth appears have only moderate consequences for poverty. In these data and within this system, growth is just not sufficient to reduce poverty substantially, at least directly. This is at odd with some of the hypotheses in the trickle down literature. When accounting for data selectivity and for the health factor, it is just not obvious that the trickle down hypothesis is directly valid for poverty alleviation. In contrast, economic growth has a massive positive influence on health levels.

In a sense, including health in the system has made obvious that this is a key determinant of the dynamic state of the system. Not only good health levels appear to be essential for high living standards, for lower poverty and for still better health conditions, but it is also the channel through which the economic growth can help to alleviate poverty substantially. This is because higher growth contributes to improve health levels, and better health reduced poverty.

Note also that this provides a different perspective in the debate about the reality of the contribution of health to growth (null for Acemoglou and Johnson (2007), positive in Blooming and Canning (2004, 2014) for example. Controlling for past levels, good health status is essential for higher levels of economic growth. In contrast, bad children health may dampen human capital accumulation.

Finally, the importance of having a dynamic view of the system first emerges through the significance of the autoregressive parameters in the GDP per capita equation and in the health equation, and much less clearly in the poverty equation perhaps.

The IRF shows that ultimately the way the system works should be analyzed dynamically, at least along with a few periods of study to allow for the multidimensional interactions to 'bite'. They show the persistence of the impact on GDP per capita and infant mortality rate after a shock on their initial levels with an acceleration over time. Furthermore, they show that the impact of an initial shock on GDP per capita leads to a decrease in the level of infant mortality that is also persistent over time. Moreover, the IRFs show clearly the importance of the health factor with the persistence of its impact on both poverty and GDP per capita, in the short and the long term.

What has been gained with the selectivity correction, and, as a consequence, the new possibility to deal with a broader set of country-year situations as usual? If one forgets the sophisticated selectivity correction, several odd-looking results would characterize the estimation. For example, the autoregressive coefficient in the poverty equation is negative; or, in the GDP per capita equation, a higher poverty would imply higher living standards. Even though they cannot be totally ruled out a priori, these ridiculously sounding features vanish when the selectivity correction is apply. Moreover, without selectivity correction, the effect of better health on economic living standards would be under-estimated. It is in fact much higher, while still significant at the 1 percent level, when the selectivity correction is applied.

However, the absence of an inequality indicator and an education indicator in the system, is a limit of our study. Indeed, this is the case since both inequality and education are shown in the literature to have important interactions with the factors of the triangle, as it was suggested by many researchers such as Ravallion (2005), Bourguignon (2004), Lorentzen, McMillan and Wacziarg (2008). The reason for this omission is that the small sample of countries and periods cannot support the identification and the estimation of a system with too many endogenously interacting factors.

7 Conclusion

The aim of this study is to investigate the interactions between the three factors of the triangle Poverty-GDP per capita-Health in developing countries. For this, we first correct for the selectivity bias from missing poverty data. Second, we combine this selectivity correction with advanced panel data econometric methods to provide an overview of the main causal interactions between the three factors.

The results shows the crucial role of the health status, as the key factor of development. Precisely, the results bring out two-way causality only between health and GDP per capita. In other words, higher levels of economic growth are associated with lower infant and child mortality rates, perhaps allowing governments to invest more in health services and medical infrastructure, which contributes to improve living conditions and to provide better health care for infants and children. On the other hand, we find evidence about the strong role played by the health factor indicating on the one hand, how much poor health people and on the other hand, can be vulnerable to poverty and in another way the importance of health human capital in the process of economic growth. However, we find no evidence about the impact of economic growth on poverty when using infant or child mortality rates as the health indicators. This makes us conclude that governments should invest more in improving health conditions and medical infrastructure, because health, in turn would lead to poverty reduction and economic growth acceleration.

Moreover, the paper suggests new research lines on the role of inequality and education which would be crucial in the development process, and also as channels through which the three factors, poverty, GDP per capita and health may interact.

Finally, one could wonder whether the estimated relationships between the three factors of the triangle are valid rather in the short or long term, which raises new questions for future research addressing stationarity and cointegration issues.

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Appendix

Among the basic assumptions of the model, it is assumed that :

$$p(y_i|\alpha_i, X_i, y_{i0}) = \frac{exp\left[y_{i+}\alpha_i + \sum_{t} y_{it} x'_{it}\beta_1 + y_{iT}(\phi + x'_{iT}\beta_2) + y_{i*}\gamma\right]}{\sum_{z} exp\left[z_{+}\alpha_i + \sum_{t} z_{it} x'_{it}\beta_1 + z_T(\phi + x'_{iT}\beta_2) + z_{i*}\gamma\right]}$$

 y_{i0} is the $y_{i(t-1)}$ for t=1. The term \sum_{z} includes all possible binary response vectors $z = (z_1, \ldots, z_T)', \ z_+ = \sum_{t} z_t, \ z_{i_*} = y_{i0} z_1 + \sum_{t>1} z_{t-1} z_t, \ y_{i+} = \sum_{t} y_{it}, \ y_{i_*} = \sum_{t} y_{i,t-1} y_{it}.$

Proving that $y_{i\downarrow}$ represents a set of sufficient statistics for α_i because y_i is conditionally independent of α_i given X_i, y_{i0} and $y_{i\downarrow}$, it can be shown that :

$$p(y_{i+}|\alpha_{i}, X_{i}, y_{i0}) = \sum_{z(y_{i+})} p(y_{i} = z | \alpha_{i}, X_{i}, y_{i0})$$
$$= \frac{exp(y_{i+}\alpha_{i})}{\mu(\alpha_{i}, X_{i}, y_{i0})} \sum_{z(y_{i+})} exp\left[\sum_{t} z_{t} x'_{it} \beta_{1} + z_{T}(\phi + x'_{iT} \beta_{2}) + z_{i_{*}} \gamma\right].$$

Then, the conditional distribution can be written as follows :

$$p(y_i|\alpha, X_i, y_{i0}, y_{i+}) = \frac{p(y_i|\alpha_i, X_i, y_{i0})}{p(y_{i+}|\alpha_i, X_i, y_{i0})} = \frac{exp\left[\sum_t y_{it} x'_{it} \beta_1 + y_T(\phi + x'_{iT} \beta_2) + y_{i*} \gamma\right]}{\sum_{z(y_{i+})} exp\left[\sum_t z_t x'_{it} \beta_1 + z_T(\phi + x'_{iT} \beta_2) + z_{i*} \gamma\right]},$$

which does not depend on α_i and becomes :

$$p(y_i|X_i, y_{i0}, y_{i\downarrow}) = \frac{exp\left[\sum_{t>1} y_{it}d'_{it}\beta_1 + y_{iT}(\phi + x'_{iT}\beta_2) + y_{i_*}\gamma\right]}{\sum_{z(y_{i\downarrow})} exp\left[\sum_{t>1} z_td'_{it}\beta_1 + z_T(\phi + x'_{iT}\beta_2) + z_{i_*}\gamma\right]} ,$$

with $d_{it} = x_{it} - x_{i1}, t = 2, ..., T$, $\sum_{z(y_{i+1})}$ includes all response configurations z with $z_+ = y_{i+1}$.

Diagram 1. The main links between Poverty, Economic growth and Health



Table 1. Summary of Effects in the Literature

	$\overline{\mathcal{T}}$		
	Poverty	Economic Growth	Health
Poverty	Ravallion 2012 (Ø)	Ravallion 2012 (-) Lopez and Serven 2009 (-)	Rajan, Kennedy and King 2013 (-) Klasen 2007 (Ø) Pe, Wall and Perrson 2000 (-)
Economic Growth	Dollar and Kraay 2002 2013 (-) Gupta and Mitra, 2004 (Ø) Bhalla, 2002 (-) Sala I Martin 2002 (-) Ravallion 2001, 2005 (-/I) Ravallion and Datt 1991 (-/I) Bourguignon 2004 (-/I)	_	Bhargava, Jamison, Lau and Murray 2001 (Ø) Younger 2001 (Ø) Pritchett and Summers 1993 (+) Hanmer, Lensink and White 2003 (+) Bhargava, Jamison, Lau and Murray 2001 (Ø) Gupta and Mitra 2004 (+) Bhargava, Jamison, Lau and Murray 2001 (Ø)
Health	Goldton and Keswell 2005 (-) Gupta and Mitra 2004 (-)	Acemoglu and Johnson 2006, 2013 (Ø) Bloom and Canning 2004, 2014 (+) Aghion, Howitt and Murtin 2011 (+/Initial level) Cervellati and Sunde 2011 (+/Demographic Transition) Bhargava, Jamison, Lau and Murray 2001 (+/Demographic Transition) Lorentzen, McMillan and Wacziarg, 2008 (+)	

The table summarizes the literature according to the effect of each variable of the triangle Poverty, Economic Growth and Health on the other. (+) denotes a significant positive effect, (ϕ) means non significant effect and. "/" means that the impact is conditional on other factors like : "/I" means that the effect of economic growth on poverty depends on the level of inequality. Moreover "/Demographic Transition" means that the impact depends on whether the country, has completed or not, the demographic transition.

				Sample	21		Sample 2 Sample 3											
		Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max	Observ	vations	Mean	Std. Dev.	Min	Max	Obser	vations
Variable																		
	overall	20,14	22,42	0,00	92,55	N = 740	25,90	25,15	0,00	92,55	N =	419	20.76	21.5764	0	81.32	$\mathbf{N} =$	231
Poverty healdcount	between		24,67	0,08	87,72	n = 112		24,89	0,08	87,72	n =	102		22,64	0,15	81,32	n =	75
with 1,25 \$ a day (%)	within		7,85	-14,07	58,15	T-bar = 4,10		8,60	-7,16	64,43	T-bar =	= 4,10		5,80	-3,17	44,58	T-bar =	= 3,08
	overall	2054,42	2068,36	50,042	14235,84	N=4085	2090,79	2124,68	68,84	12770,19	N = 7	719	2513,09	2544,65	68,84	12770,19	$\mathbf{N} =$	231
Gdp per Capita (\$)	between		1995,60	160,21	9804,20	n=112		2081,83	152,65	10015,60	n =	108		2419,12	145,70	11482,05	n =	75
	within		619,61	-1801,39	6486,07	T-bar=6,60		554,02	-1259,92	4845,38	T-bar =	= 6,65		428,85	618,33	4080,35	T-bar	= 3,04
Infant mortality	overall	55,92	37,08	3,70	174,40	N=4615	56,59	37,91	4,93	171,30	N =	796	47,98	34,22	5,23	159,40	N =	231
(per 1000)	between		33,06	9,08	144,09	n=137		34,42	9,33	139,93	n =	111		31,45	6,03	127,69	n =	75
	within		17,11	-14,45	129,99	T-bar=30,48		15,36	-9,45	108,43	T-bar =	= 7,17		10,52	0,87	97,99	T-bar	= 3,10
	overall	82.46	64.97	4.90	335.70	N = 4615	84.07	66.86	6.38	328.68	N =	796	69.50	57.37	6.63	239.03	N =	231
Infant mortality under 5 (per 1000)	between		58 33	11 37	245 76	n = 137	,	61 17	11.68	230.59	n =	111	,	53 62	7 71	215.60	n =	75
(per 1000)	within		20.01	50.10	218.01	T = 137		26.36	21.60	182.16	T bar -	-7.17		17.25	5 41	148.86	T bar	- 3 10
	withiii		29,01	-59,10	210,91	1-0ai = 33,70		20,30	-21,00	102,10	1-0a1 =	- /,1/		17,23	-5,41	140,00	1-Dal	- 5,10
Life expectancy at birth	overall	62,15	9,54	26,76	79,85	N = 4387	61,71	9,50	28,33	79,09	N =	818	67,08	7,86	40,94	79,09	N =	231
(years)	between		8,85	39,87	76,72	n = 137		8,84	39,70	76,63	n =	113		9,01	44,63	77,51	n =	75
	within		3,66	33,38	79,08	T-bar = 32,02		3,38	44,00	77,30	T-bar =	= 7,24		1,60	61,60	74,44	T-bar =	= 3,08

Sample 1 is the annual complete panel data for the period 1980-2013 and 137 developing countries. Sample 2 is the same sample after dividing the period of study into 8 periods of 4 years. Sample 3 is the sample after selecting only the available poverty abservations from sample 2 and countries with at least three available observations. N is the total number of observations, n is the number of countries and T-bar is the number of average periods of observation.

		Sample 1	Sample 2			
Region	% sample	% Poverty observations available	% sample	% Poverty observations available		
East Asia and Pacific	15,2	13,67	10,88	11,93		
Europe and Central Asia	13,92	21,97	15,89	21,48		
Latin America and Carribean	18,63	35,84	19,07	24,11		
Middle East and North Africa	8,5	4,95	9,66	8,11		
South Asia	6,11	4,32	6,23	7,16		
Sub Saharan Africa	37,65	19,25	38,26	27,21		

Table 3. Sample composition by region

Sample 1 is the annual complete panel data for the period 1980-2013 and 137 developing countries. Sample 2 is the same sample after dividing the period of study into 8 periods of 4 years and some data cleaning. % sample is the percentage of the countries from a given region of the total number of developing countries from all the regions of the world. % Poverty observations available is the percentage of available poverty observations in any region of the world from the total number of available poverty observations in the whole developing world.

Fixed effects model	ita	Bartolucci and Nigro model Logit fixed effects					
Lagged ODF per capi	ita	Dummy variable (Survey	incidence)				
	(1)		(2)	(3)			
Independent variable	Coefficient	Independent variable	Coefficient	Coefficient			
Lagged Conflict	-0,074** (0,023)	Lagged Conflict	-0,218 (0,179)	-0,453 (0,157)			
Lagged Democracy	0,008** (0,036)	Lagged Democracy	0,055** (0,049)	0,168*** (0,009)			
Lagged Disasters	-0,060* (0,087)	Lagged Disasters	1,098 *** (0,000)	1,088** (0,027)			
Lagged Instrument (<i>IV_{GDP}</i>)	-0,135*** (0,005)	Lagged GDP per capita	2,182* (0,092)	0,675 (0,192)			
Constant	6,661*** (0,000)	Residuals from (1)	-1,715 (0,121)				
		Lagged Dependent Variable	0,455 ** (0,042)	-0,446** (0,023)			

Table 4. Model of Survey Incidence

The Conflict indicator is a dummy variable constructed from the Uppsala Conflict Data Program (UCDP), 2012. Democracy indicator is from the Polity IV Project 2010 (Center for Systemic Peace). Disasters are from (EM-DAT). The other indicators are from WDI. IV_{GDP} : Price of oil* (± 1) if the country is exporter or importer of oil. * denotes significance at the 10 % level, ** denotes significance at the 5% level, *** denotes significance at the 1% level. P-values are reported in parentheses. N is the total number of observations, n is the number of countries.

Table 5. Poverty Equation

		FE3SLS	(endogeneity, simultaneity an	nd selectivity)
		Dependent variab	le: Ln(Poverty healdcount in	dex with 1,25 \$ a day)
Independent Variable	(1)	(2)	(3)	(4)
Ln(Lag_Poverty healdcount index with 1,25 \$ a day))	-0,519*** (0,000)	0,115 (0,215)	0,063 (0,490)	-0,300*** (0,001)
Ln(Lag_Gdp per capita)	-4,055*** (0,000)	-0,195 (0,613)	-0,339 (0,381)	-2,390*** (0,000)
Ln(Lag_Infant mortality)		2,480*** (0,000)		
Ln(Lag_Infant mortality under 5)			2,288*** (0,000)	
Ln(Lag_Life_expectancy at birth)				-10,914*** (0,000)
Lag_Inverse-Mills ratio	3,678 (0,000)	4,046*** (0,000)	4,441*** (0,000)	4,472*** (0,000)
Country FE	YES	YES	YES	YES
Sargan Test		33,712 (0,038)	33,712 (0,038)	38,708 (0,01)
L		N=231, n=75		

	Fixe	ed Effects m	odel tv)	Fixed	d Effects mo	del with logeneity)		FE2SLS model	[7]	H H	FE3SLS mode No selectivity	el v)
	(III	o endogener		Simula	neity (no end	iogeneity)			,,	(-		,,
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Independent Variable						< / <		`				`
Ln(Lag_Poverty Headcount)	0,075	0,408***	0,081	0,369***	0,366***	0,380***	0,322**	0,319**	0,350**	-0,156**	-0,245***	-0,618***
With 1,25\$ a day	(0,260)	(0,000)	(0,272)	(0,000)	(0,000)	(0,000)	(0,045)	(0,048)	(0,045)	(0,040)	(0,001)	(0,000)
Ln(Lag_Gdp per capita)	-0,244	-0,254	-0,728***	-0,264	-0,280	-0,788***	0,017	0,018	-0,585	-0,061	-0,293	-2,492***
	(0,208)	(0,189)	(0,000)	(0,171)	(0,147)	(0,000)	(0,971)	(0,969)	(0,214)	(0,874)	(0,443)	(0,000)
							1.000 dubut					
Ln(Lag_Infant mortality)	0,766***			0,805***			1,222***			2,299***		
	(0,000)			(0,000)			(0,000)			(0,000)		
Ln(Lag Infant mortality under												
5)		0,687***			0,723***			1,101***			2,037***	
		(0,000)			(0,000)			(0,000)			(0,000)	
Ln(Lag_Life_expectancy at												
birth)			-1,635*			-1,777*			-4,964**			-7,266***
			(0,101)			(0,074)			(0,043)			(0,000)
Constant FE	VEC	VEC	VEC	VEC	VEC	VEC	VEC	VEC	VEC	VEC	YES	VEC
Country FE	1ES	TES	TES	TES	N-221	r=75	TES	1ES	TES	TES		1 ES

Table 7. GDP per capita Equation

Γ		FE3SLS (e	endogeneity, simultaneity and	selectivity)
		Depe	endent variable: Ln(Gdp per ca	apita)
Independent Variable	(1)	(2)	(3)	(4)
Ln(Lag_Poverty healdcount index with 1,25 \$ a day))	0,141* (0,081)	0,066 (0,382)	0,059 (0,451)	0,039 (0,642)
Ln(Lag_Gdp per capita)	1,308*** (0,000)	0,794*** (0,000)	0,806*** (0,000)	1,113*** (0,000)
Ln(Lag_Infant mortality)		-0,522*** (0,000)		
Ln(Lag_Infant mortality under 5)			-0,487*** (0,000)	
Ln(Lag_Life_expectancy at birth)				2,917*** (0,001)
Lag_Inverse-Mills ratio	-0,629 (0,223)	-0,910* (0,093)	-1,085* (0,058)	-1,679** (0,025)
Country FE	YES	YES	YES	YES
Sargan Test	-	29,367 (0,105)	29,367 (0,105)	25,468 (0,227)
		N=231, n=75		1

Table 8. GDP per capita Equation Comparisons

	Fixed E (no er	affects mode adogeneity)	1	Fixed Effects model with simultanei (no endogeneity)			F (Ne	E2SLS mod o simultanei	el ty)	FE3SLS model (No selectivity)		
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Lag_Poverty Headcount) With 1,25\$ a day	0,026 (0,800)	0,026 (0,798)	-0,003 (0,917)	-0,008 (0,749)	-0,006 (0,824)	-0,011 (0,662)	0,029 (0,722)	0,026 (0,749)	-0,055 (0,495)	0,114* (0,101)	0,114* (0,104)	0,120* (0,083)
Ln(Lag_Gdp per capita)	0,775*** (0,000)	0,780*** (0,000)	0,882*** (0,000)	0,767*** (0,000)	0,773*** (0,000)	0,873*** (0,000)	0,615*** (0,000)	0,609*** (0,000)	0,695*** (0,000)	0,731*** (0,000)	0,739*** (0,000)	1,009*** (0,000)
Ln(Lag_Infant mortality)	-0,246*** (0,000)			-0,231*** (0,000)			-0,399*** (0,000)			-0,487*** (0,000)		
Ln(Lag_Infant mortality under 5)		-0,218*** (0,000)			-0,209*** (0,000)			-0,363*** (0,000)			-0,438*** (0,000)	
Ln(Lag_Life_expectancy at birth)			1,001***			0,981***			1,676***			1,928***
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
	N=231, n=75											

Table 9. Health Equation

		FE3SLS (endogeneity, simultaneity and	nd selectivity)
	Dependent variable: Ln(Infant mortality)	Dependent variable: Ln(Infant mortality under 5)	Dependent variable: Ln(Life expectancy at birth)
Independent Variable	(1)	(2)	(3)
Ln(Lag_Poverty healdcount index with 1,25 \$ a day))	0,034 (0,338)	0,042 (0,275)	-0,016** (0,043)
Ln(Lag_Gdp per capita)	-0,170* (0,060)	-0,190* (0,056)	-0,201 (0,461)
Ln(Lag_Infant mortality)	0,957*** (0,000)		
Ln(Lag_Infant mortality under 5)		0,934*** (0,000)	
Ln(Lag_Life_expectancy at birth)			1,033*** (0,000)
Lag_Inverse-Mills ratio	0,323 (0,309)	0,331 (0,360)	-0,201** (0,023)
Country FE	YES	YES	YES
Sargan Test	17,935 (0,652)	17,935 (0,652)	29,972 (0,092)
	N=231, r	n=75	

Table 10. Health Equation Comparisons

	Fixe (n	ed Effects mod to endogeneity	lel)	Fixed I simultane	Effects mode eity (no endo	l with geneity)	F (N	E2SLS mod o simultanei	el ty)	FI (N	FE3SLS model (No selectivity)		
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Ln(Lag_Poverty healdcount index With 1,25\$ a day	0,018 (0,588)	-0,010 (0,621)	0,001 (0,915)	-0,006 (0,720)	-0,009 (0,660)	0,001 (0,918)	-0,044 (0,468)	-0,045 (0,507)	-0,003 (0,831)	0,006 (0,743)	0,014 (0,432)	0,000 (0,873)	
Ln(Lag_Gdp per capita)	-0,125*** (0,006)	-0,142*** (0,006)	0,008 (0,366)	-0,123*** (0,006)	-0,141*** (0,006)	0,008 (0,355)	-0,303** (0,012)	-0,349*** (0,011)	0,026 (0,295)	-0,189** (0,026)	-0,215** (0,023)	0,014 (0,248)	
Ln(Lag_Infant mortality)	0,957*** (0,000)			0,952*** (0,000)			0,871*** (0,000)			0,922*** (0,000)			
Ln(Lag_Infant mortality under 5)		0,943*** (0,000)			0,941*** (0,000)			0,846*** (0,000)			0,897*** (0,000)		
Ln(Lag_Life_expectancy at birth)			0,896*** (0,000)			0,896*** (0,000)			0,754*** (0,000)			0,852*** (0,000)	
Country FE	YES	YES	YES	YES N=231	YES	YES	YES	YES	YES	YES	YES	YES	

Table 11. Robustness check (Poverty Equation)

			FE.	3SLS (endoger	neity, simultan	eity and selectiv	ity)		
	Ins	trumentation	2	l	Instrumentation	n 3	(Control variab	oles
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Lag_Poverty healdcount index with 1,25 \$ a day	0,181* (0,061)	0,143 (0,135)	-0,208** (0,025)	0,115 (0,235)	0,070 (0,462)	-0,062 (0,566)	-0,040 (0,793)	-0,097 (0,516)	-0,537*** (0,000)
Ln(Lag_Gdp per capita)	-0,318 (0,403)	-0,421 (0,271)	-2,203*** (0,000)	-0,794** (0,034)	-0,986*** (0,008)	-2,293*** (0,000)	-0,736 (0,229)	-0,895 (0,150)	-3,046*** (0,000)
Ln(Lag_Infant mortality)	2,481*** (0,000)			2,186*** (0,000)			2,072*** (0,000)		
Ln(Lag_Infant mortality under 5)		2,320*** (0,000)			1,986*** (0,000)			1,882*** (0,000)	
Ln(Lag_Life_expectancy at birth)			-12,273*** (0,000)			-13,764*** (0,000)			-5,139 (0,141)
Lag, Inverse-Mills ratio	4,707*** (0,000)	5,175*** (0,000)	5,231*** (0,000)	4,762*** (0,000)	5,197*** (0,000)	6,610*** (0,000)	4,464*** (0,001)	4,891*** (0,000)	6,332*** (0,000)
Ln(Adolescent_Fertlity)							1,458** (0,017)	1,579*** (0,010)	2,735*** (0,000)
Voice_Accountability							0,794 (0,213)	0,779 (0,226)	0,541 (0,462)
Corruption							-0,646 (0,203)	-0,664 (0,196)	-1,372** (0,014)
Ln(Rural_population)							-3,736*** (0,000)	-3,840***	-3,415*** (0,000)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Instrumentation (2) gives the interaction of the amount of aid for both health and poverty with the donor countries' crisis (with a positive or negative sign depending on whether there was crisis or not), Instrumentation (3) includes just the amount of foreign aid for health as health instrument and female headed households as poverty instrument. For both instrumentation, we keep the price of oil, as instrument for Gdp per capita.

Table 12. Robustness Check (GDP per capita equation)

	FE3SLS (endogeneity, simultaneity and selectivity)								
	Instrumentation 2			Instrumentation 3			Control variables		
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Lag_Poverty healdcount index with 1,25 \$ a day))	0,106 (0,176)	0,104 (0,197)	0,130 (0,130)	0,172* (0,078)	0,165* (0,088)	0,232** (0,034)	0,084 (0,484)	0,084 (0,489)	0,017 (0,893)
Ln(Lag_Gdp per capita)	0,865*** (0,000)	0,879*** (0,000)	1,196*** (0,000)	0,884*** (0,000)	0,902*** (0,000)	1,218*** (0,000)	0,714 (0,000)	0,730*** (0,000)	0,835*** (0,000)
Ln(Lag_Infant mortality)	-0,521*** (0,000)			-0,553*** (0,000)			-0,359* (0,073)		
Ln(Lag_Infant mortality under 5)		-0,494*** (0,000)			-0,509*** (0,000)			-0,340*** (0,066)	
Ln(Lag_Life_expectancy at birth)			3,097*** (0,002)			4,399*** (0,000)			1,887*** (0,089)
Lag, Inverse-Mills ratio	-1,089* (0,062)	-1,275** (0,037)	-1,744*** (0,021)	-0,970 (0,145)	-1,123* (0,094)	-1,650** (0,037)	-0,818 (0,171)	-0,947 (0,127)	-1,512* (0,080)
Ln(Adolescent_Fertlity)							-0,280** (0,020)	-0,283** (0,020)	-0,273** (0,039)
Political stability							-0,084 (0,394)	-0,075 (0,458)	-0,045 (0,701)
Private_sector_Development							0,127 (0,496)	0,125 (0,508)	0,212 (0,346)
Ln(Rural_population)							-0,115 (0,826)	-0,094 (0,858)	-0,514 (0,274)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Instrumentation (2) gives the interaction of the amount of aid for both health and poverty with the donor countries' crisis (with a positive or negative sign depending on whether there was crisis or not), Instrumentation (3) includes just the amount of foreign aid for health as health instrument and female headed households as poverty instrument. For both instrumentation, we keep the price of oil, as instrument for Gdp per capita.

	FE3SLS (endogeneity, simultaneity and selectivity)									
	Instrumentation 2			Instrumentation 3			Control variables			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Independent Variable										
Ln(Lag Poverty healdcount index with 1,25 \$ a day))	0,042	0,053	-0,014*	0,062	0,079*	-0,016**	-0,053	-0,062	-0,008	
	(0,228)	(0,169)	(0,070)	(0,145)	(0,093)	(0,043)	(0,297)	(0,278)	(0,508)	
Ln(Lag_Gdp per capita)	-0,162*	-0,183*	0,015	-0,163	-0,171	0,019	-0,278**	-0,290**	0,038	
	(0,070)	(0,063)	(0,324)	(0,125)	(0,147)	(0,225)	(0,022)	(0,029)	(0,110)	
Ln(Lag_Infant mortality)	0,969*** (0,000)			0,987*** (0,000)			0,825*** (0,000)			
Ln(Lag Infant mortality under 5)		0 947***			0 976***			0 794***		
En(Eug_intaite mortuney under 5)		(0,000)			(0,000)			(0,000)		
Ln(Lag_Life_expectancy at birth)			0,991***			0,990***			0,813***	
			(0,000)			(0,000)			(0,000)	
Lag.Inverse-Mills ratio	0.401	0.434	-0.176**	0.644*	0.736*	-0.201**	0.448	0.423	-0.211*	
	(0,202)	(0,228)	(0,039)	(0,084)	(0,083)	(0,022)	(0,238)	(0,321)	(0,081)	
L n(A dologoont Fortlity)							0.210*	0.258*	-0.075	
Ln(Addiescent_Ferinty)							(0,092)	(0,064)	(0,180)	
							0.064	0.104	0.017	
Voice_Accountability							- ,	- 7 -		
							(0,603)	(0,453)	(0,703)	
Corruption							-0,119*	-0,125	0,027	
							(0,100)	(0,127)	(0,197)	
L n(Pural nonvertion)							0.129	0.152	0.040	
							(0,377)	(0,393)	(0,329)	
		. The								
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	

Table 13. Robustness check (Health equation)

Instrumentation (2) gives the interaction of the amount of aid for both health and poverty with the donor countries' crisis (with a positive or negative sign depending on whether there was crisis or not), Instrumentation (3) includes just the amount of foreign aid for health as health instrument and female headed households as poverty instrument. For both instrumentation, we keep the price of oil, as instrument for Gdp per capita.

